

When Do Megawatts Become Alpha? A Conditional Transmission Framework Linking Renewable Energy Deployment to the Equity Returns of Renewable Energy Firms

Soham Jain

McLean High School
1633 Davidson Rd, McLean, VA 22101
sohamluhadia@gmail.com

Abstract

Global renewable power capacity is expected to almost double between 2025 and 2030, and many investors expect to earn higher equity returns from the physical expansion of the renewable energy industry as a whole. Clean-energy stocks, however, lost around 40% of their value between 2021 and the end of 2023, while renewables grew at a record pace. This paper examines whether renewable energy-related firms' stock prices in the U.S. reflect growth in renewable energy activity. The study starts with the conditional transmission framework, which holds that market, interest-rate, industry, and policy conditions need to be favorable for deployment to translate into shareholder returns, and directly examines the unconditional relationship. The monthly return of the Nasdaq Clean Edge Green Energy Index (CELS) is regressed against the monthly change in the 10-year real Treasury yield in the U.S., the monthly U.S. market excess return, and the monthly growth of U.S. renewable electricity generation, which is used as a proxy for physical renewable activity rather than for new capacity, using ordinary least squares regression in JASP on 229 observations from December 2006 to December 2025. The model accounts for 59.6% of the variability in CELS returns. The excess return of the whole market was found to be significant ($B = 1.541$, $p < .001$), indicating that the shares of clean-energy firms tend to move about 1.5 times as much as the market. As hypothesized, the real-yield coefficient is negative, but it is not statistically significant ($p = .328$), and growth of renewable generation is not significantly related to returns ($p = .949$). The findings suggest that growth in megawatts does not necessarily lead to returns for shareholders, and they have policy and investor implications and can feed into further research on funding the energy transition.

Keywords: renewable energy, clean-energy stocks, energy transition, stock returns, real interest rates, market beta, regression analysis

Introduction

Renewables are widely forecast to keep growing. The International Energy Agency (IEA) estimates that the capacity of renewables will rise by some 4,600 gigawatts across the world from 2025 to 2030, about double the amount added in the previous five years, and that renewable energy will account for 43% of global electricity generation by 2030, up from 32% in 2024 (IEA, 2025). About 80% of this growth is expected to be from solar photovoltaic (IEA, 2025). Many investors have drawn a simple conclusion from this: companies that are building, owning, and operating renewable assets should earn higher stock returns because of how their business is expanding. This is the reason that a substantial amount of money went into clean-energy funds, with 2020 seeing inflows of \$25.9 billion and 2021 \$28.1 billion (Sturgeon, 2024). That conclusion is complicated by what followed. By late 2023, the S&P Global Clean Energy Index had fallen by about 40% from its 2021 highs, and more than \$280 billion had been withdrawn from clean-energy stocks (Milewski, 2023). The decline came despite annual renewable additions setting records and the passage of the Inflation Reduction Act, the largest U.S. climate-investment law to date. Deployment and

shareholder wealth moved in opposite directions. This disconnect implies that the relationship between megawatts and market value works through a transmission mechanism that can strengthen, weaken, or even reverse it.

Previous studies only partially tackle that mechanism. Comparative analysis of renewable and fossil fuel portfolios has demonstrated that over the longer time horizon renewables outperform fossil fuels, but it has not clarified when this is not the case (IEA & Imperial College Business School, 2021). Previous studies on market connectedness have identified the relationship between the prices of clean-energy stocks and the price of oil, as well as with the rest of the financial markets (Ferrer et al., 2018). Even though the expected returns of green stocks are lower than those of less green stocks, when climate change concern suddenly increases, the realized returns of green stocks are high (Pástor et al., 2021, 2022). These all culminate in a conditional view: growth in deployment yields returns to shareholders only when interest rates, industry structure, and policy are favorable. This is called a conditional transmission framework in this paper. In simple terms, the framework is a series of links from a new megawatt to a return to the shareholder. Favorable overall market conditions decide whether an investor is willing to pay for growth at all, low real interest rates increase the present value of the long-lived cash flows renewable projects produce, the structure of the industry decides whether the firms that build and operate the assets keep the value created, and stable policy decides whether expected subsidies and demand are delivered. If any one of these links fails, more deployment can result in a flat or declining share price.

This study takes up the issue by exploring the simplest case of the growth thesis in the context of the United States. What this paper adds to the existing literature on renewable-energy stocks is a direct test of whether a measure of physical renewable activity carries any information about clean-energy equity returns once the market and the real interest rate are controlled for, which earlier work on the performance and connectedness of these stocks has not done. It investigates whether growth in renewable electricity generation in the United States is discernible in the monthly returns of U.S.-traded clean-energy stocks after adjusting for the general movement of the stock market and the real interest rate. The monthly returns of the Nasdaq Clean Edge Green Energy Index (CELS) are regressed against excess returns of the equity market, the growth rate of renewable electricity generation, and the change in the real 10-year Treasury yield from December 2006 to December 2025. Specifically, the research question is: do monthly returns of U.S.-listed clean-energy stocks co-move with growth in renewable electricity generation in the United States, over and above the market excess return and the monthly change in the real interest rate?

Literature Review

Long-horizon evidence of the performance of renewable energy equities is provided in a joint IEA/Imperial College Business School report, which created listed-equity portfolios of renewable energy companies and fossil fuel companies for global, advanced-economy, and emerging-market samples. The total return of renewable portfolios exceeded the total return of fossil fuel portfolios over the preceding decade, and the volatility of the renewable portfolios was lower for the global sample and the advanced-economy sample (IEA & Imperial College Business School, 2021). The above is backed by country studies in individual periods and markets. Wan et al. (2021) examined 201 listed energy companies in China at the time of the COVID-19 outbreak and found that the outbreak negatively affected fossil fuel companies more than clean-energy companies, and that the attention of investors boosted the returns of clean-energy firms only. Subsequently, Ansaram and Petitjean (2024) expanded this to 25 countries and found that renewable energy prices and consumption, in addition to fossil fuel prices, are significant determinants of the stock

performance of energy companies. A deficiency of this literature is that it considers returns realized within specific periods. It cannot tell the difference between outperformance that investors are likely to continue to receive and outperformance that is a result of unexpected one-time events.

A second body of work examines the links between renewable equities and traditional energy and financial markets. Ferrer et al. (2018) demonstrated that the relationship between crude oil prices and renewable energy stock returns is not stable over time or across investment horizons and is more pronounced for shorter investment periods. Substantial and time-varying spillovers between the indices of fossil and renewable energy were also found in further studies, which use connectedness methods (Caporale et al., 2023). Empirical evidence based on the quantile approach suggests that fossil fuel markets have a significant negative effect on renewable assets under extreme market conditions, while renewable assets can serve as a short-term safe haven (Ozcelebi et al., 2024). Other research on renewable energy tokens finds an average interconnectedness of around 30%, increasing in periods of crisis (Attarzadeh, 2025). This means that a large proportion of the variation in the sector's returns comes from outside the sector. Renewable growth can, at best, be one of the factors determining returns, and its impact needs to be measured after controlling for the general market, as was done in this research.

The theoretical basis of a conditional view comes from research on green asset pricing. When investors prefer to invest in green assets, the price of green assets increases and their expected return decreases compared to less green assets, according to Pástor et al. (2021). However, when concern about the environment strengthens unexpectedly, green assets can provide better realized returns. This is confirmed empirically in the U.S. by Pástor et al. (2022), who found that the unusually high returns of U.S. green stocks in the late 2010s were driven by unexpected increases in climate concern rather than by high expected returns. Bolton and Kacperczyk (2021) have a complementary result: investors demand a premium for bearing carbon-transition risk. Ardia et al. (2023) created an index of climate change concern based on media coverage and demonstrated that green stocks outperform their brown peers when climate change concern is higher than expected. This literature suggests that a forecast of high deployment does not always mean better expected returns, because growth that investors already anticipate is already priced in.

There are three more pieces of evidence on the conditions under which growth can fail to reach shareholders. The first is the structure of the industry. Solar manufacturing capacity was projected to exceed 1,100 GW by the end of 2024, more than double expected demand, while solar module prices fell by some 50% after the start of 2023, resulting in substantial manufacturing losses (IEA, 2024). Overcapacity has been mentioned as one of the factors accounting for the poor performance of the sector in the past years (Baselli, 2024). In a commoditized industry, the price cuts that accelerate deployment also reduce producer margins. The second factor is the cost of capital. Interest rates affect the value of renewable projects because they require large initial investment and their cash flows extend over decades. Higher policy rates in the U.S. during 2022 and 2023 imposed costs on renewable valuations, and lower rates alone do not guarantee a recovery of investment (Jain, 2024). Furthermore, the bubble detection analysis of Giancaterini et al. (2025) identifies periods of speculative dynamics in green indices between 2020 and 2021. The third condition is policy risk. Within a single year, the IEA reduced its projections for renewable capacity growth in the U.S. by almost half as a result of the accelerated rollback of federal tax credits and other restrictions (DiGangi, 2025; IEA, 2025).

Although each of the strands gives a partial explanation, few studies have directly related a measure of physical renewable activity to equity returns when other factors such as the stock market and interest rates are controlled. The conditional transmission framework this study draws on combines these strands. It holds

that the effect of renewable growth on returns depends on whether firms are able to capture the value they create, the interest-rate environment, policy stability, and whether the growth was already expected by investors. The first step in assessing the framework is to see if there is any unconditional relationship at all. The hypotheses are mentioned in the section below.

Methodology

Research Design

This study uses a quantitative research design. It is a time-series analysis that tests the relationship between the monthly returns of a U.S.-listed clean-energy equity index and three explanatory variables, using multiple linear regression estimated by the ordinary least squares (OLS) method.

Area and Scope of Study

This study is limited to the United States. There are 229 monthly observations taken from December 2006 to December 2025. The published history of the CELS index begins on November 20, 2006, so the November 2006 month-end value is the base and the first monthly return is the return for December 2006. The end date is the final full calendar year of data from all four data sources. The CELS index is a modified market-capitalization-weighted index of companies making, developing, distributing, or installing clean-energy technologies, and it started on November 17, 2006, at a base value of 250 (Clean Edge, n.d.). The index is listed and traded in the U.S., but not all the companies that make up the index are based there.

Data Sources

Secondary data were analyzed from four public sources, all obtained on October 10, 2026. Daily closing values for the CELS index, 4,807 trading days from November 20, 2006, to December 31, 2025, were taken from Nasdaq Global Indexes (Nasdaq, n.d.). Daily observations for the same period of the yield on 10-year inflation-indexed U.S. Treasury securities (series DFII10) were taken from the FRED database of the Federal Reserve Bank of St. Louis (Board of Governors of the Federal Reserve System, n.d.). The monthly excess return on the U.S. market and the one-month Treasury bill rate came from the Fama/French three-factor file in the Kenneth R. French Data Library (French, n.d.), which is based on the factor definitions of Fama and French (1993). Monthly net electricity generation by source from all sectors in the United States, from December 2005 to December 2025, was obtained from Table 7.2a of the Monthly Energy Review published by the U.S. Energy Information Administration (EIA, 2026). The generation series begins one year earlier than the others to allow the year-over-year growth measure used in the robustness checks; its solar component covers utility-scale facilities only.

Variables Used

The monthly return on the CELS index (R_CELS) was used as the dependent variable. The independent variables were the monthly change in the 10-year real Treasury yield (D_REAL_AVG), the U.S. market excess return (MKT_RF), and the month-to-month growth in U.S. renewable electricity generation (G_RE_MOM). G_RE_MOM measures the electricity actually produced by renewable sources, not additions to installed capacity; it is used here as an observable monthly proxy for physical renewable activity, and the difference between generation and deployment is returned to in the Findings and Limitations.

Table 1: Definitions, Units, and Sources of the Variables

Variable	Definition	Unit	Source
R_CELS	Monthly return on the Nasdaq Clean Edge Green Energy Index (price index): last closing value of the month divided by the last closing value of the previous month, minus 1	Decimal	Nasdaq
D_REAL_AVG	Change in the monthly average of the daily 10-year inflation-indexed Treasury yield (DFII10) from the previous month	Percentage points	FRED
MKT_RF	U.S. market return minus the one-month Treasury bill rate (Mkt-RF), divided by 100	Decimal	Kenneth R. French Data Library
G_RE_MOM	Month-to-month growth in U.S. renewable net electricity generation (conventional hydroelectric, wood, waste, geothermal, solar, and wind)	Decimal	EIA Monthly Energy Review, Table 7.2a
R_CELS_EX	R_CELS minus the one-month Treasury bill rate (robustness check)	Decimal	Nasdaq; French Data Library
D_REAL_EOM	Change in DFII10 from the last trading day of the previous month to the last trading day of the current month (robustness check)	Percentage points	FRED
G_RE_YOY	Growth in renewable generation relative to the same month one year earlier (robustness check)	Decimal	EIA Monthly Energy Review, Table 7.2a

Data Processing

One monthly variable was created for each raw series. The CELS return is the closing index value on the last trading day of the month divided by the closing value on the last trading day of the previous month, minus 1. For December 2006, for example, the return was $242.41 / 250.59 - 1 = -0.0326$. All yields published on a daily basis for the month were averaged, and the variable is the difference between the average yield for the month and the average yield of the previous month, in percentage points. The market excess return was taken directly from the Fama/French file and divided by 100 to convert it from a percentage to a decimal. Renewable generation was obtained by adding conventional hydroelectric, wood, waste, geothermal, solar, and wind generation, and its growth was calculated as the total for the current month divided by the total for the previous month, minus 1.

The four monthly variables were subsequently merged by calendar month. The final dataset contained 229 observations, there were no missing values, and no values were interpolated or estimated. The changes in the real yield are in percentage points, and returns and growth rates are in decimals ($0.05 = 5\%$). All calculations were performed using spreadsheet formulas linked to the raw downloaded values and were independently recalculated. To double-check, the daily CELS values from Nasdaq were compared with the same index published by FRED, and the two matched on all 4,807 trading days.

Model Specification

The regression model that is estimated can be stated as:

$$(R_CELS)_t = \beta_0 + \beta_1(D_REAL_AVG)_t + \beta_2(MKT_RF)_t + \beta_3(G_RE_MOM)_t + \varepsilon_t$$

Here $(R_CELS)_t$ is the return on the CELS index in month t , β_0 is the intercept, β_1 , β_2 , and β_3 are the coefficients to be estimated, and ε_t is the error term. According to the hypotheses, β_1 will be negative and β_2 and β_3 will be positive.

The classical linear regression procedure was used to estimate the model in JASP (Version 0.98.1; JASP Team, 2026). The three predictors were entered as covariates (the Enter method) and R_CELS was entered as the dependent variable. A coefficient was considered statistically significant when its two-sided p value was below .05.

Hypotheses

H_1 : There is a negative relationship between the real interest rate and clean-energy equity returns.

H_2 : The overall stock market return is positively associated with the return of clean-energy stocks.

H_3 : Growth in renewable electricity generation is positively associated with clean-energy equity returns.

Diagnostic Tests

A few diagnostic tests were conducted to ensure the reliability of the model. To check for multicollinearity, the tolerance value, the variance inflation factor (VIF), and collinearity diagnostics based on eigenvalues and condition indices were used. The Durbin–Watson test was used to check for autocorrelation among the residuals. The linearity and the constancy of the variance of the residuals were checked visually in a plot of residuals against the predicted values. R^2 , the root mean square error (RMSE), and the Akaike and Bayesian information criteria (AIC and BIC) were used to compare the model fit with an intercept-only model.

Robustness Checks

To determine whether the results depended on how the variables were measured, three alternative specifications were estimated, each changing one variable at a time. The first change was to use the CELS return in excess of the one-month Treasury bill rate (R_CELS_EX), making it comparable to the market excess return. Second, the real-yield change was measured from the last day of trading in the previous month to the last day of trading in the current month (D_REAL_EOM), the same period as the stock return. Third, the growth in generation relative to the same month of the previous year (G_RE_YOY) was used as the measure of growth, thus eliminating the seasonal pattern in hydro, wind, and solar output. Further, the baseline model was re-estimated using Newey–West standard errors with six lags (Newey & West, 1987), which are still valid in the presence of autocorrelated residuals. The robustness regressions were estimated using OLS on the same dataset in Python with the statsmodels library (Seabold & Perktold, 2010), and all of them are summarized in one table (Table 8).

Analysis

Descriptive Statistics

Table 2: Descriptive Statistics for the Study Variables

Variable	N	M	SD	SE
R_CELS	229	0.008038	0.09249	0.006112
MKT_RF	229	0.008474	0.04585	0.003030
D_REAL_AVG	229	−0.001715	0.1859	0.01228
G_RE_MOM	229	0.009725	0.09719	0.006422

Note. R_CELS, MKT_RF, and G_RE_MOM are decimals (0.01 = 1%). D_REAL_AVG is in percentage points.

Table 2 reports descriptive statistics for the four variables across the 229 monthly observations. The CELS index earned a mean monthly return of 0.80% (SD = 9.25%), close to the mean market excess return of 0.85% (SD = 4.59%). Clean-energy equities were therefore about twice as volatile as the broad market without earning a higher average return. The mean monthly change in the real yield was close to zero (−0.002 percentage points, SD = 0.186), which indicates no persistent trend over the sample. Renewable generation grew by 0.97% per month on average, and its large standard deviation (9.72%) reflects strong seasonal variation.

Regression Model

Table 3: Model Summary for the Regression of CELS Returns

Model	R	R ²	Adjusted R ²	RMSE	AIC	BIC
M ₀	0.000	0.000	0.000	0.09249	−437.445	−430.578
M ₁	0.772	0.596	0.590	0.05920	−638.820	−621.652
Model	R ² change	df1	df2	p	Autocorrelation	Durbin–Watson (p)
M ₀	0.000	0	228		0.04100	1.917 (.527)
M ₁	0.596	3	225	< .001	0.1666	1.665 (.010)

Note. M₀ is the intercept-only model. M₁ includes MKT_RF, D_REAL_AVG, and G_RE_MOM. RMSE = root mean square error; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Table 3 compares the intercept-only model (M₀) with the full model (M₁). The three predictors jointly explained 59.6% of the variance in monthly CELS returns (R² = .596, adjusted R² = .590), a statistically significant improvement over M₀ ($\Delta R^2 = .596$, $p < .001$). The root mean square error fell from 0.0925 to 0.0592, and the lower AIC and BIC values confirm the better fit of M₁. The Durbin–Watson statistic of 1.665 ($p = .010$) indicates mild positive first-order autocorrelation in the residuals ($r = .167$), so the standard errors should be interpreted with some caution.

Analysis of Variance

Table 4: Analysis of Variance for the Full Model

Model	Source	Sum of squares	df	Mean square	F	p
M ₁	Regression	1.162	3	0.3873	110.5	< .001
	Residual	0.7887	225	0.003505		
	Total	1.951	228			

Note. M₁ includes MKT_RF, D_REAL_AVG, and G_RE_MOM.

Table 4 presents the analysis of variance for the full model, which tests whether the three predictors together explain a significant share of the variation in CELS returns. Of the total sum of squares (1.951), the regression accounted for 1.162 and the residual for 0.789. The resulting test was significant, $F(3, 225) = 110.5$, $p < .001$. The null hypothesis that all slope coefficients are jointly equal to zero is therefore rejected, which indicates that the model as a whole has explanatory power for clean-energy equity returns.

Regression Coefficients

Table 5: Regression Coefficients and Collinearity Statistics

Model	Term	B	SE	β	t	p	Tolerance	VIF
M ₀	(Intercept)	0.008038	0.006112		1.315	.190		
M ₁	(Intercept)	-0.005077	0.003996		-1.271	.205		
	MKT_RF	1.541	0.08680	0.7636	17.75	< .001	0.971	1.030
	D_REAL_AVG	-0.02094	0.02139	-0.04209	-0.9793	.328	0.973	1.028
	G_RE_MOM	0.002581	0.04039	0.002712	0.06389	.949	0.998	1.002

Note. B = unstandardized coefficient; SE = standard error; β = standardized coefficient; VIF = variance inflation factor.

Table 5 reports the estimated coefficients. The market excess return was the only statistically significant predictor ($B = 1.541$, $SE = 0.087$, $\beta = .764$, $t = 17.75$, $p < .001$): a one-percentage-point rise in the market excess return was associated with a 1.54-percentage-point rise in the CELS return. The change in the real yield carried the hypothesized negative sign but was not statistically significant ($B = -0.021$, $p = .328$), and renewable generation growth was also not statistically significant ($B = 0.003$, $p = .949$). The intercept was also non-significant ($p = .205$), which indicates no abnormal return once the predictors are controlled for. Tolerance values above .97 and VIF values close to 1 indicate that multicollinearity is not a concern.

Regression Equation

Table 6: Fitted Regression Equations

Model	Equation
M ₀	$R_CELS = 0.008$
M ₁	$R_CELS = -0.005 + 1.541 \text{ MKT_RF} - 0.021 \text{ D_REAL_AVG} + 0.003 \text{ G_RE_MOM}$

Table 6 expresses the two fitted models as equations. The intercept-only model predicts a constant monthly return of 0.008, which equals the sample mean of CELS returns. The full model combines the intercept with the three estimated slopes. To illustrate, in a month with a market excess return of 2%, no change in the real yield, and no growth in renewable generation, the model predicts a CELS return of approximately 2.6%. The equation shows that predicted returns are driven almost entirely by the market term, because the remaining coefficients are small and statistically indistinguishable from zero.

Multicollinearity Test

Table 7: Collinearity Diagnostics for the Full Model

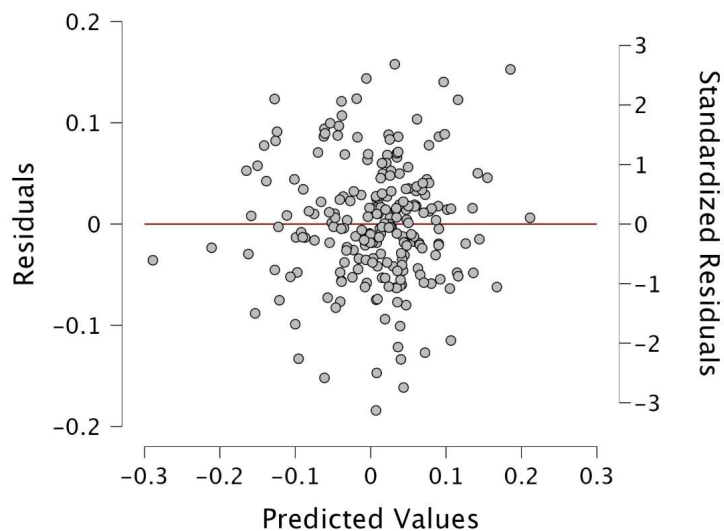
Dimension	Eigenvalue	Condition index	(Intercept)	MKT_RF	D_REAL_AVG	G_RE_MOM
1	1.286	1.000	0.224	0.311	0.117	0.092
2	1.039	1.113	0.131	0.036	0.458	0.314
3	0.9151	1.186	0.287	0.034	0.153	0.593
4	0.7597	1.301	0.359	0.620	0.273	0.001

Note. The last four columns are variance proportions.

Table 7 provides collinearity diagnostics based on the eigenvalues of the predictor matrix. The four eigenvalues were all close to 1 (0.760 to 1.286), and the condition indices ranged from 1.000 to 1.301, below the values of 15 to 30 conventionally taken to signal a collinearity problem. No dimension showed high variance proportions for two or more predictors at once. Together with the VIF values in Table 5, these results indicate that the three predictors are nearly independent of one another, so each coefficient can be interpreted separately.

Residual Analysis

Figure 1: Residuals Versus Predicted Values for the Full Model



Note. Standardized residuals from the full model (M_1) are plotted against the model's predicted values for the 229 monthly observations from December 2006 to December 2025. The horizontal line marks a residual of zero. A random scatter around this line with a roughly constant vertical spread indicates that the assumptions of linearity and constant residual variance are reasonable.

Figure 1 plots the residuals of the full model against its predicted values. The points are scattered around the zero line with no curved pattern, which supports the assumption of a linear relationship. The vertical spread of the residuals is broadly similar across the range of predicted values, which gives no clear visual evidence of heteroscedasticity, although observations are sparse at the extremes. Most standardized residuals lie within ± 2 , and only one exceeds 3 in absolute value (January 2024), which suggests that the results are not driven by a small number of outliers.

Robustness Checks

Table 8: Regression Results Under Alternative Variable Definitions

Predictor	(1) Baseline	(2) Excess-return DV	(3) Month-end yield	(4) Year-over-year growth
Market excess return	1.541*** (0.087)	1.542*** (0.087)	1.536*** (0.089)	1.541*** (0.087)
Change in real yield	-0.021 (0.021)	-0.021 (0.021)	-0.014 (0.018)	-0.021 (0.021)
Renewable generation growth	0.003 (0.040)	0.003 (0.040)	0.002 (0.040)	0.009 (0.041)
Intercept	-0.005 (0.004)	-0.006 (0.004)	-0.005 (0.004)	-0.006 (0.005)
R ²	.596	.596	.595	.596
Adjusted R ²	.590	.590	.590	.590
N	229	229	229	229

Note. Unstandardized coefficients with standard errors in parentheses. Column 1 repeats the baseline model. Column 2 uses the CELS return minus the risk-free rate as the dependent variable (DV). Column 3 measures the change in the real yield from month-end to month-end. Column 4 measures generation growth against the same month one year earlier. Newey–West (six-lag) p values for the baseline model in column 1: market excess return < .001; change in real yield .317; renewable generation growth .933. ***p < .001.

The results are not sensitive to the measurement of the variables, as shown in Table 8. In every specification the market coefficient remained close to 1.54 and significant at the .001 level, while the real-yield and generation-growth coefficients remained small and non-significant (p values between .323 and .970). There was little difference in the explained variance among the four models. The results were similar when the baseline model was re-estimated using Newey–West standard errors, which account for the autocorrelation observed in Table 3: the excess return on the market was still significant (p < .001), and the change in the real yield (p = .317) and generation growth (p = .933) were not significant.

Findings

The main result of this study is the size and stability of the market exposure of clean-energy stocks. The market coefficient of 1.54 indicates that the CELS index moved about one and a half times as much as the market during a particular month, and the coefficient is nearly identical in all four specifications in Table 8.

Overall, these findings imply that the majority of the monthly performance fluctuation in clean-energy stocks listed in the U.S. is attributable to fluctuation in the overall stock market. This supports H_2 . When this market exposure is controlled for, neither the change in the real interest rate nor renewable electricity generation growth had a statistically significant relationship with returns.

H_1 is not supported in this sample: the real-yield coefficient is negative, as theory suggests, but it is not statistically significant, so no conclusion about the direction of the effect can be drawn from these data. This may be due to the fact that changes in interest rates affect the whole stock market, and to a certain degree this effect is already reflected in the market variable. H_3 is also not supported: there was no statistically significant evidence of growth in renewable generation having an impact on same-month equity returns. This aligns with the conditional transmission framework and with Pástor et al. (2021), who argued that growth that investors are anticipating is already priced in.

There are two caveats to the findings. First, monthly growth in generation measures the output of existing renewable assets, not the deployment of new capacity, so it is an imperfect measure of deployment. It varies with weather and season, covers only utility-scale solar, and is published about two to three months after the month it covers. The findings suggest there is no measurable connection between this measure and returns, but that does not mean deployment cannot have an impact. Second, the Durbin–Watson test indicated that there was mild positive autocorrelation of the residuals, which could result in underestimated ordinary standard errors. The Newey–West results reported above indicate that this does not affect the overall conclusions.

Limitations

Some of the companies in the CELS index are not U.S.-based, and it is a price index without dividends. Electricity generation is output (not new capacity) and is influenced by weather and seasonal conditions. The regression identifies relationships within the same month but cannot establish causation. Future research might consider using capacity additions instead of generation, analyzing industry segments separately (such as solar manufacturers, project developers, and grid operators), adding interaction terms to explore whether the effect of deployment changes across lower-rate and higher-rate periods, and adding a climate concern measure. These extensions would test the conditional transmission framework more fully and would aid in clarifying when megawatts translate to returns for shareholders.

Conclusion

The purpose of this study was to see whether growth in renewable electricity generation in the U.S. is reflected in the monthly returns of clean-energy stocks listed on U.S. exchanges. The model explains approximately 60% of the variance in returns over 229 months from December 2006 to December 2025, and almost all of this is due to movements in the overall stock market. Clean-energy stocks behaved as a relatively high-beta segment of the market, moving about 1.5 times as much as the overall market, with neither growth in generation nor changes in real yields providing any statistically significant new information. The results have implications for practice. They suggest that putting money into a broad clean-energy index has been more like holding an amplified position in the stock market than a stake in clean-energy development. The growth forecast should therefore not be seen as a reliable indicator of the returns that can be expected. For policymakers, the findings are in line with the view in the literature that financing the energy transition relies on capital-market conditions as well as deployment speed.

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